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# Machine Learning Based Activity Recognition To Identify Wasteful Activities In Production

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**Abstract**

Lean Management focusses on the elimination of wasteful activities in production. Whilst numerous methods such as value stream analysis or spaghetti diagrams exist to identify transport, inventory, defects, overproduction or waiting, the waste of human motion is difficult to detect. Activity recognition attempts to categorize human activities using sensor data. Human activity recognition (HAR) is already used in the consumer domain to detect human activities such as walking, climbing stairs or running. This paper presents an approach to transfer the human activity recognition methods to production in order to detect wasteful motion in production processes and to evaluate workplaces. Using sensor data from ordinary smartphones, long-term short-term memory networks (LSTM) are used to classify human activities. Additional to the LSTM-network, the paper contributes a labeled data set for supervised learning. The paper demonstrates how activity recognition can be included in learning factory training starting from the generation of training data to the analysis of the results.



*Keywords:* Articificial intelligence; Digital Manufacturing System; Machine learning; Learning; Operations management

## 1. Introduction

Lean Management is a customer-centered production philosophy that relies on the elimination of waste in order to constantly improve production. Apart from the overarching guiding principles of waste reduction and customer orientation Lean Management provides a wide range of established methods to detect and eliminate wasteful activities [12]. Digitization and Industry 4.0 transform the working environment in almost all industrial companies. Despite the increasing degree of automation, human workers will play a role in future production. Nonetheless, it is expected that the role of humans in production shifts towards a role of knowledge workers. Consequently, technology in production should assist by reducing complexity and identifying wasteful activities [4]. As a result, the skill requirements change and additional qualification is necessary for a successful digital transformation [6]. Whilst waste in transport, inventory, waiting, over-processing and overproduction are easily detectable, waste of motion is due to its ephemeral nature

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difficult to identify. Artificial intelligence (AI) currently receives much attention in research and industry. Significant advances in fields such as natural language processing and image recognition have led to high expectations for AI applications in an industrial context [8]. This paper contributes an approach how to integrate machine learning in a learning factory curriculum in order to build up realistic expectations towards AI applications in production. It also demonstrates the capacities of AI-based applications to assist workers in the detection of waste of motion.

## 2. Related Work

Human activity recognition (HAR) stands for deducing human activities based on sensor data [18]. The sensor data is analyzed for patterns that can be attributed to a set of known human activities. Lara and Labrador provide an overview of human activities that are currently detectable mostly in the areas of transport, fitness, military and ambulation [7]. Whilst camera-based data collection systems are limited to a predefined range, mobile sensor devices have unlimited range. Smartphones and wearables have a high autonomy and are thus capable of collecting and analysing data over longer time periods. Depending on the activity acceleration, orientation and other movement-related signals are used. These can be enriched by environment parameters such as temperature, noise or humidity. Many successful applications of HAR use machine learning for pattern recognition due to its ability to generalize. To capture the temporal dependencies between the data recurrent neural networks (RNN) as well as long short term memory (LSTM) are often applied [9].

Chen et. al. contributed an LSTM-based approach to detect human motion activities by analyzing tri-axial accelerometer data. The published approach attains a 92.1 % accuracy on the publicly available WISDM data set [3]. The WISDM data set includes acceleration values of 29 persons generated by different Android Smartphones [15].

Subasi et. al. focus on the improvement of the accuracy. Their research assesses the quality of different isolated machine learning classificators, including support vector machines, random forest, k-nearest-neighbor and an AdaBoost approach. AdaBoost is a machine learning meta model that aggregates the results of individual machine learning approaches. Each individual machine learning approach has been trained on a different part of the test data set. To derive the final classification the individual results have been aggregated using a simple majority quorum. The authors demonstrated that AdaBoost was capable of improving the overall accuracy on the publicly available REALDISP (REAListic sensor DISPlacement) data set to 99.98 % [13]. REALDISP records acceleration, rate of turn, magnetic field and quaternions under realistic conditions including displacements [11].

The research of Pärkkä et. al. places the emphasis on a realistic data set of human ambulation activities. The research team evaluates different locations of the sensors on the human body as well as a variety of sensors including environment sensors and devices for capturing vital signals such as heart rate or skin resistance. The test group was performing a set of different activities at different locations. The evaluation was based on a decision tree. The results showed that the acceleration data was most decisive. Surprisingly, the vital signals only played a minor role in activity recognition [10].

The impact of the sensor location on the human body is addressed by Sztyler et. al.. Their approach is based on a hierarchical classification that determines the location of the sensor before the actual activity recognition problem. Following this approach, a high accuracy is attainable whilst maintaining the flexibility of alternative sensor placements and thus the use of smartphones or wearables [14].

There are various approaches to human activity recognition focusing on ambulation using highly available devices such as smartphones and smartwatches. The application however is not in the production context. The available data sets as well as the existing findings make HAR an ideal problem to demonstrate how AI can be applied in a production context to identify wasteful activities and to raise awareness on the limitations and possibilities of AI in Lean Management.

## 3. Human Activity Recognition

The project was conducted following the CRISP-DM reference model [16]. For the remainder of this paper, the steps will only be discussed partially. The objective of the undertaking was to identify the percentage of waiting (standing), sitting, walking and jogging during a production day in order to identify the waste of motion in activities as starting point for an assessment of the work environment regarding ergonomic design. The data should be collected using Android smartphones. The results of the project should be integrated in learning factory trainings targeting students as well as industry at GAMI, Global Advanced Manufacturing Institute, KIT China branch in Szuhou, China. The trainees should be able to evaluate their own motion patterns and to supply their own data for the training of the LSTM network to witness the effects of training data to the resulting accuracy. The trainees have an engineering background but no specific knowledge in data analytics. The learning objectives are to gain practical experience with data driven analysis and to build an understanding of the possibilities and limitations of data-driven approaches in combination with Lean.

### *3.1. Data understanding and data preparation*

To verify the overall performance of the developed model compared to other approaches the WISDM data set [15] will be used. Additionally, a secondary data set will be created using Android smart phones to train and evaluate the model. This data set will be used in trainings and can be expanded by the trainees.

#### *3.1.1. WISDM data set*

The WISDM data set includes 1.098.207 data points of 29 test persons performing the activities walking (38.6%), jogging (31.2%), climbing stairs up (11.2%), climbing stairs down (9.1%), sitting (5.5%) and standing (4.4%) [17]. The activities climbing stairs up and down have been removed from the data set.

#### *3.1.2. GAMI data set*

The GAMI data set consists of the four target activities walking, waiting (standing), jogging and sitting. To collect the data, ten test persons have been asked to sit and stand for 90 seconds and to walk and jog for 200 meters. Each activity was followed by 90 seconds rest for better data separation. The data was recorded using an Android smartphone. The individual data sets have been aggregated and labeled. The data set is publicly available [5]. The data shows only marginal differences in the patterns between the activities sitting and standing however the acceleration direction is different, for details see figure 1.

For the activity recognition, the data has been split up into segments using a sliding window with a delta of 50 data points. This approach maintains the temporal connection between the data points. In case a segment contains more then one activity, the segment is labeled with the predominant activity. The data set has been split up into two separate sets for training (2/3) and validation (1/3).

### *3.2. Modelling - LSTM-based Human Activity Recognition*

The activity recognition is based on an LSTM network. The input values for the x, y and z accelerations of each segment are fed into a multi-layer LSTM network of four layers of 32 nodes each followed by a dropout layer. The dropout layer deletes temporarily nodes during the training and thus changes the network topology to prevent overfitting. Additionally, early stopping was used. The training ends if the current accuracy does not improve the best accuracy over all trainings by at least 0.001 in three subsequent periods. The structured evaluation of 144 hyperparameter combinations identified the following parameters: learning rate: 0.001, dropout rate: 0.5, batch size: 64, activation function: tanh, optimizer: Adam. For detailed information on the retained network configuration see figure 2.

## 4. Experimental results

In this section the experimental results both on the WISDM as well as on the GAMI data set are presented.

### *4.1. Evaluation - WISDM data set*

Figure 3 shows the accuracy per epoch and the loss. The accuracy on the training as well as test set increases constantly and reaches its maximum after five epochs. The loss function is of inverse shape. The confusion matrix reveals a good performance. The most common error occurs between the activities walking and jogging. Sitting and standing is only confused half as often. The overall accuracy was 98.34 %.

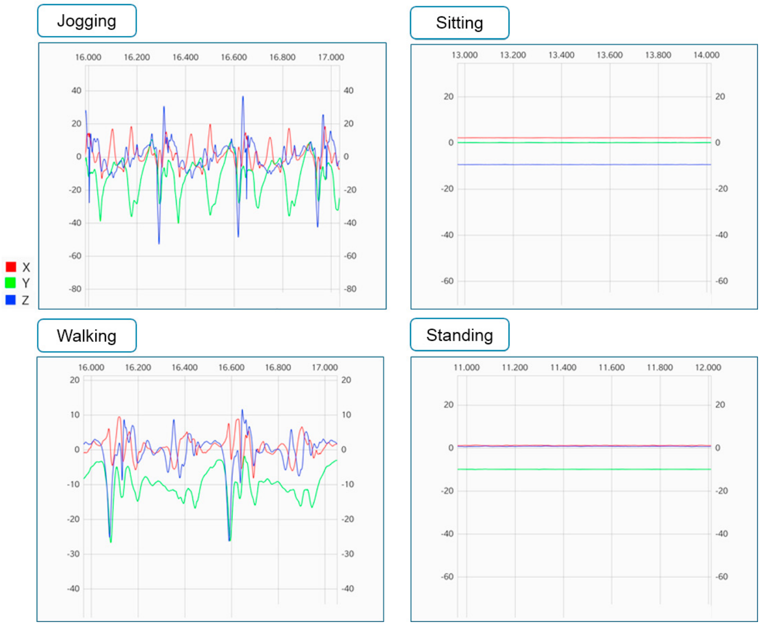


Fig. 1. Plot of the activities jogging, sitting, walking and standing from the GAMI data set.

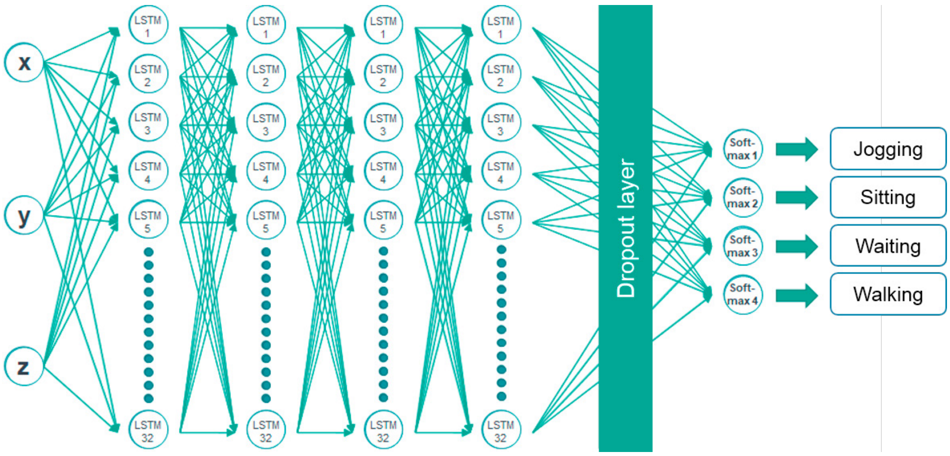


Fig. 2. LSTM network configuration.

### 4.2. Evaluation - GAMI data set

The results obtained on the GAMI test set can bee seen in figure 4. Compared to the data collected in a laboratory environment of the WISDM data set the achieved accuracy is slightly lower with 96,81 %. The shape of the accuracy and loss curve are comparable. Similar to the WISDM data set, the classification of jogging and walking is error prone. In total 114 segments belonging to jogging were wrongly labeled as walking. The opposite error is less frequent with 51 occurrences.

### 4.3. Deployment and teaching concept

The described model has been integrated and deployed in the digital layout planning tool Planium. The trainees follow the CRISP-DM model covering the data collection step, the training as well as the evaluation. Using the described


Fig. 3. (left) Accuracy and loss on the WISDM data set; (right) Confusion matrix of the WISDM data set after the last epoch.

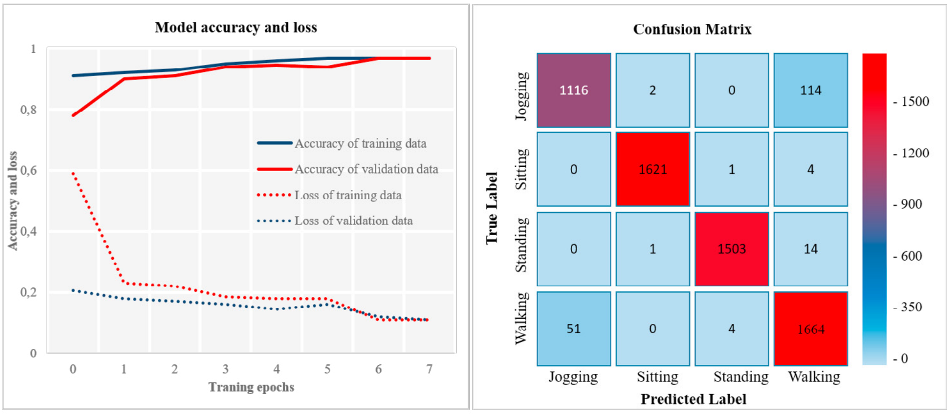


Fig. 4. (left) accuracy and loss on the GAMI data set; (right) Confusion matrix of the GAMI data set after the last epoch.

deep learning model, the participants train the algorithm with the GAMI test data and vary hyper-parameters such as the learning rate. To evaluate the deployed model, the participant collect their own sample data using ordinary smart-phones and upload the data in the software tool to see their evaluation. Having identified wasteful activities regarding motion, they adapt the design of the production either by designing the workstations according to 5S principles to reduce wasteful activities and by adapting the layout or shifting work content between work stations. Regarding the question of which ratio of activities is ideal, the proposed approach does not provide an answer. The results gained by this approach are only a starting point for a thorough analysis of the workplace. However, the system provides quantitative data and therefore paves the way for comparisons and fact-driven workplace assessments. To evaluate the impact of the design of a workstation on the human body, dedicated camera-based approaches such as [2] generating digital body models are better-suited. However, these evaluations require high efforts and are limited to a smaller environment.

Experiments have shown a high accuracy of the deployed model in the real use case. Figure 5 shows a screenshot of the evaluation of a data set recorded by a trainee. The raw data has been analyzed to identify the correct classification. The error was 2% for walking and 1.85% for standing, 0.14% for sitting and 0% for jogging.

## 5. Conclusion

This paper demonstrates how well-researched machine learning approaches for activity recognition can be applied to a production scenario to enrich Lean Management. To target the qualification gap regarding knowledge on machine

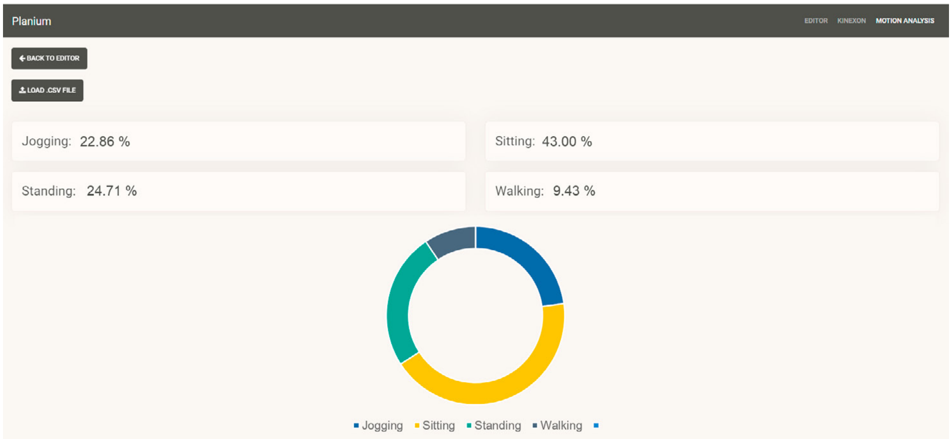


Fig. 5. Integration of the data analysis model in the software tool Planium for workshops.

learning the system is integrated in a learning factory training. The participants experiment with a given learning model, record test data and evaluate their data. Future research could focus on how the actual development of a machine learning model could be included in trainings making the development of these tools accessible.

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